Manifold-preserving single-image super-resolution based on collaborative representation support

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Abstract

Nowadays, super-resolution is becoming more and more important in most optical imaging systems and image processing applications due to current resolution limit of charged couple device (CCD) and complementary metal-oxide semiconductor (CMOS). In this paper, we proposed a novel single-image super-resolution algorithm, which combines collaborative representation into manifold-preserving approach. The main contributions of our work can be summarized into two points. First, supporting bases which are used to calculate the mapping relationship between low-resolution (LR) images and high-resolution (HR) images are obtained by applying collaborative representation on the neighborhoods of the dictionary atoms, where the neighborhoods are clustered from the whole training sample pools. Second, to achieve a balance between execution speed and reconstruction quality, a global solution for our framework is constructed by transferring the online calculating process to offline. We demonstrate better results on commonly used datasets, showing both better visual performance and higher index values compared to other methods.

Keywords Optical imaging systems · Super-resolution · Manifold preserving · Collaborative representation

1 Introduction

Images and videos are very important for normal communication, information transmission and surveillance systems. These contents appear more and more frequently with the rapid development of hand-held imaging device. However, most images suffer from the degradation process due to image blurring caused by the point spread function (PSF) of the imaging system and atmospheric turbulence, aliasing from subsampling and noise. To easily solve these problems, super-resolution (SR) emerges as the times require [1].

The SR problem is extremely ill-posed since multiple HR images can be mapped to the same LR image through a degradation model. Thus, the reconstruction process should rely on strong prior information. Through the years, researchers have proposed various methods to solve this problem, they can be roughly divided into two categories: multiple-frame

super-resolution [2–5] and single-image super-resolution (SISR) [6]. The SISR approaches also can be further divided into interpolation-based methods [7–9], reconstruction-based methods [10–14] and learning-based methods [15, 16]. Among all these approaches, the learning-based SR method is considered as one of the most effective solutions, it works by learning the mapping relationship between LR and HR image pairs as the image prior that should be used for reconstruction.

Representative learning-based works such as neighbor embedding (NE) [17–19], which assumes that LR and HR patches have locally similar geometry on low-dimensional nonlinear manifolds, thus allow the estimated HR output patch to share the same interpolation coefficients that are used to approximate the corresponding input LR patch on an existing database. However, NE needs to search a vast dataset for image patterns that are similar to the complicated structures of the input images, thus will consume huge time cost. By utilizing machine learning, Yang et al. [20, 21] treated the LR and HR patches as a sparse linear combination of the jointly learned LR and HR dictionary atoms based on the assumption that LR and HR patches share the same sparse representation coefficients [22]. Although this method obtains superior results with remarkably low

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computational complexity, it is still limited by the strong constraint of same sparse representation and time cost of L_1 -norm regularity in the optimization process. Zeyde et al. [23] developed this framework by applying K-SVD [24, 25] on LR dictionary training, utilizing principle component analysis (PCA) and orthogonal matching pursuit (OMP) [26] for sparse representation. This method shows substantial improvements in terms of running speed and reconstruction quality. Moreover, Jiang et al. [27] combined neighbor embedding with sparse representation theory, utilizing a manifold-preserving framework on a sparse support base and learning a local regression as a mapping function from LR to HR. This method which is named as manifold-regularized sparse support regression (MSSR) also achieves pleasing results. However, the support base is obtained by applying OMP on the LR dictionary [28], which may make the precision of manifold insufficient for predicting the HR version of an input LR image, and the online process is still time consuming.

In this paper, we are inspired by MSSR, and propose a new algorithm named manifold-regularized collaboration representation support (MCSR) to solve super-resolution problem. Compared to the previous work of [27], our main contributions are threefolds. First, by reformulating the SR problem as an L_2 -norm-regularized least squares regression and applying collaboration representation on it, we can obtain a projective matrix offline. Then the matrix is multiplied by the input LR image to obtain the support base which is used to calculating the final mapping relationship between the input LR patch and its HR version. Different from calculating sparse support base in online process, our approach can boost online execution speed. Second, the collaboration representation is constructed on the training sample pool for each atom in the dictionary, thus the selected support base is much closer to the input LR image and the manifold will be approximated better. Third, to achieve a fast execution speed, we further transfer of the whole online process including manifold preserving and support base calculating to offline. We take experiments on commonly used datasets, showing better results of sharper edges, finer textures and higher index values compared to other methods.

The remainder of this paper is organized as follows: In Sect. 2, we take a close look at the MSSR approach. In Sect. 3, we present the proposed MCSR method and describe its details. In Sect. 4, we report experimental results. In Sect. 5, we conclude the paper.

2 Related works

In this section, we make a short review about the previous work of MSSR approach.

Considering the manifold assumption in NE (manifolds spanned by LR and HR patches have locally similar geometry) and strong constraint in sparse coding-based SR (LR and HR patches share the same sparse representation coefficients) may not be feasible in practical [29], the MSSR focuses on learning a much more stable LR-to-HR mapping function in the support domain where the same sparse representation constraint is relaxed, together with preserving the geometry for the reconstructed HR patch space. By denoting the original HR image patches as $X = [x_1, x_2, \dots, x_k]$, $x_k \in R^D$ and corresponding LR patches as $Y = [y_1, y_2, \dots, y_k]$, $y_k \in R^d$, where D and d are dimensions of HR and LR patch, the objective function of MSSR can be written as follows:

$$O_{\text{MSSR}} = \sum_i \varepsilon(P, y_i, x_i) + \alpha \|P\|_H^2 + \beta \|P\|_M^2, \quad (1)$$

where $\varepsilon(P, y_i, x_i) = \sum_{i \in S} (Px_i - y_i)^2$ is a predefined loss function of support samples, $\|P\|_H^2$ is a regularization function measuring the smoothness of parameter P , and $\|P\|_M^2$ is an appropriate penalty term that should reflect the intrinsic structure of data. The parameter α controls the complexity of function in ambient space while β controls the complexity of function along geodesics in intrinsic geometry of data space.

The goal of MSSR is to minimize the loss function term by finding a function $f(y, P) = Py$ which maps an input LR patch y_{in} to its corresponding HR version. In this term, i is the indices of nonzero elements in the coding coefficients of patch y_{in} on the LR dictionary, the sparse support domain is constructed by these elements and thus denoted as S , where $i \in S$. The support sample sets can be defined as X_S and Y_S . For the manifold-preserving term $\|P\|_M^2$, since the data manifold M is unknown, the geometry relation is preserved using L_1 graph [30]. This is to sparsely approximate the HR patch on the smooth patch manifold space by a linear combination of a few nearby patches, which should refer to the support domain X_S . Any HR patch x_i can be approximated by data matrix X_S except x_i as follows:

$$\begin{aligned} \hat{W}_i &= \arg \min_{W_i} \|x_i - X_S W_i\|_2 + \lambda_1 \|W_i\|_1, \\ \text{s.t. } W_{ii} &= 0 \end{aligned} \quad (2)$$

where W_i denotes the i -th column of the edge weight matrix W whose diagonal elements are zeros, and λ_1 is the parameter balancing the coding error of x_i and the sparsity of W_i . Then the geometry constraint can be preserved from W for $PY_S W_i$ by

$$\begin{aligned} \sum_{i \in S} \|Py_i - PY_S W_i\|_2^2 &= \|PY_S - PY_S W\|_F^2 \\ &= \|PY_S(I - W)\|_F^2, \end{aligned} \quad (3)$$

where I is an identity matrix. Considering above-mentioned two properties, the objective function is defined as

$$O_{\text{MSSR}} = \|PY_S - X_S\|_F^2 + \alpha \|P\|_F^2 + \beta \|PY_S(I - W)\|_F^2. \quad (4)$$

Using matrix properties $\text{tr}(BA) = \text{tr}(AB)$, $\|A\|^2 = \text{tr}(AA^T)$, and $\text{tr}(A) = \text{tr}(A^T)$, we have

$$O_{\text{MSSR}} = \text{tr}(PY_S Y_S^T P^T - PY_S X_S^T - X_S Y_S^T P^T + X_S X_S^T) + \alpha \text{tr}(PP^T) + \beta \text{tr}(PY_S G Y_S^T P^T), \quad (5)$$

where $G = (I - W)(I - W)^T$. Then we take the derivate of O_{MSSR} with respect to P and set it to zero; thus

$$P(Y_S Y_S^T + \alpha I + \beta Y_S G Y_S^T) = X_S Y_S^T. \quad (6)$$

Finally, by solving the objective function, the algebra solution is given by

$$P = X_S Y_S^T (Y_S Y_S^T + \alpha I + \beta Y_S G Y_S^T)^{-1}. \quad (7)$$

The MSSR remarkably improved the image reconstruction quality from SC- and NE-based methods. However, the manifold that is preserved is constructed by the sparse vectors, which are selected using OMP. This may make the manifold not have enough precision. Moreover, the final post-processing step of using iterative back projection is not recommended since it may produce displeasing artifacts [23]. And the complicated computing process also makes MSSR very time consuming.

3 Manifold-regularized collaboration representation support (MCSR)

In this section, we will present the details of our proposed algorithm. We fix the magnification factor to 3.

3.1 Collaboration representation support

As we have mentioned in Sect. 2, MSSR uses the OMP algorithm to select the most contributive vectors that can represent the input LR image from the LR dictionary. The problem is that OMP calculates the inner product between dictionary atoms and the input LR patch, and can promise that the residual is always orthogonal to the previous selected atoms. Let a_1 and a_2 be the first two atoms selected by OMP to represent the input LR patch y_{in} and r_1 be the residual after this step, r_1 should be orthogonal to a_1 and a_2 . After next projection, OMP will obtain the third atom vector a_3 and the next residual r_2 , with r_2 being orthogonal to a_1 , a_2 , and a_3 . Therefore, these vectors are not closest to y_{in} , but best sparsely represent y_{in} , thus the manifold approximated by them will not be precise enough.

Inspired by [31], we treat this problem using collaboration representation instead of sparse coding. Using the L_2 norm can encourage the weight parameters to be infinitely close to 0, which is less likely to produce an overfitting than the L_1 norm. So in our framework, the sparse constraint is reformulated as a least squares regression by the L_2 -norm, with the following expression:

$$\min_{\theta} \|y_{\text{in}} - N_L \theta\|_2^2 + \lambda_2 \|\theta\|_2, \quad (4)$$

where θ is the coefficient, λ_2 is a weighting parameter balances the two terms and N_L is the corresponding LR neighborhood of the input patch feature y_{in} . By grouping K nearest neighbor for each dictionary atom from the whole training sample pool, N_L can refer to the neighborhood of the atom that are most similar to y_{in} . Using collaborative representation, the algebraic solution is obtained by

$$\theta = (N_L^T N_L + \lambda_2 I)^{-1} N_L^T y_{\text{in}} = P_C y_{\text{in}}, \quad (5)$$

where the projective matrix

$$P_C = (N_L^T N_L + \lambda_2 I)^{-1} N_L^T, \quad (6)$$

can be computed offline for each atom in the dictionary. Then we can obtain the support base by applying P_C to y_{in} instead of solving sparse coding problem, thus boosting the online execution speed. Note that θ is not sparse, so we choose the most contributive J vectors as our support base, denoting as X_C and Y_C . And since all the vectors in the support base are chosen from the nearest neighborhood, the manifold will be approximated much better than using sparse support base. Using X_C as support domain in the manifold-preserving step, we can obtain the final objective function:

$$O_{\text{MCSR}} = \|PY_C - X_C\|_F^2 + \alpha \|P\|_F^2 + \beta \|PY_C(I - W)\|_F^2, \quad (7)$$

and the projective matrix can be obtained by following expression:

$$P = X_C Y_C^T (Y_C Y_C^T + \alpha I + \beta Y_C G Y_C^T)^{-1}. \quad (8)$$

This matrix is then applied to the input y_{in} , mapping it to the final corresponding HR version. Note that the iterative back projection is not needed in our framework due to the high precision and smoothness of the manifold. The complete procedure of MCSR is introduced in Algorithm 1.

Algorithm 1 Image Super-resolution via MCSR

- 1: **Input:** Training sample pool and LR test image Y_{in} , regularization parameters $\lambda_1, \lambda_2, \alpha$ and β .
- 2: Train LR and HR dictionaries using sparse coding method as [20] does.
- 3: Cluster the nearest neighborhood and calculate the projective matrix P_C according to Equation (7) for each atom in the dictionary.
- 4: **for** each patch y_{in} of Y_{in} **do**
 - a) Select the closest dictionary atom for y_{in} .
 - b) Apply the corresponding projective matrix P_C of the atom to y_{in} , obtain the collaborative representation coefficients θ .
 - c) Obtain the support samples X_C and Y_C from the most contributive vectors in θ .
 - d) Construct the HR patch manifold and obtain the similarity matrix according to Equation (2).
 - e) Preserve the manifold geometry and obtain the mapping matrix P according to Equation (9).
 - f) Apply P to y_{in} , obtain the HR version.
- 5: **end for**
- 6: Obtain the HR image X_{out} by integrating all the reconstructed HR patches and averaging pixel values in overlap regions.
- 7: **Output:** HR reconstructed image X_{out} .

3.2 Global solution and offline processing

Although we succeed in reducing the running time using our framework, the online time cost is still not pleasing for the practical use due to the manifold-preserving process. In our experiment, we find that with more vectors being chosen as support base, the algorithm will become more time consuming. The reconstruction quality also will improve to a peak, and then it will slowly drop down as Fig. 1 shows. We notice that when the vector number J in the support base is same as the neighborhood size K , the support domain is equal to the corresponding neighborhood. Therefore, by denoting the new support domain as X_N and Y_N , the manifold-preserving process can be transferred to offline by the following expression:

$$P = X_N Y_N^T (Y_N Y_N^T + \alpha I + \beta Y_N G Y_N^T)^{-1}. \quad (9)$$

The final projective matrix can be computed offline for each dictionary atom. We only need to find the atom which is closest to our input patch y_{in} , and the HR result can then be obtained by applying the corresponding projective matrix to y_{in} . Using the global solution, we will obtain very fast online execution speed together compared to the original MCSR method with a small support domain. The detailed process is depicted in Algorithm 2.

Fig. 1 The average performance of MCSR on Set14 images using different number of support vector

Algorithm 2 Image Super-resolution via MCSR (global version)

- 1: **Input:** Training sample pool and LR test image Y_{in} , regularization parameters $\lambda_1, \lambda_2, \alpha$ and β .
- 2: Train LR and HR dictionaries using sparse coding method as [20] does.
- 3: **for** each atom a_d in the LR dictionary **do**
 - a) Cluster the nearest neighborhood of a_d from the whole training sample pool and using it as our support samples X_N and Y_N .
 - b) Construct the HR patch manifold and obtain the similarity matrix according to Equation (2).
 - c) Preserve the manifold geometry and obtain the mapping matrix P according to Equation (9).
- 4: **end for**
- 5: **for** each patch y_{in} of Y_{in} **do**
 - a) Select the closest dictionary atom for y_{in} .
 - b) Apply the corresponding projective matrix P_C of the atom to y_{in} , obtain the HR version patch.
- 6: **end for**
- 7: Obtain the HR image X_{out} by integrating all the reconstructed HR patches and averaging pixel values in overlap regions.
- 8: **Output:** HR reconstructed image X_{out} .

4 Experimental results

In this section, we give the experimental results of our proposed MCSR method, and compare it to other algorithms in terms of peak signal-to-noise ratio (PSNR) and structural similarity (SSIM).

To ensure a fair comparison, we obtain our dictionary on the same training dataset of 91 images as proposed by Yang et al. [20] and fix the size of dictionary to 1024 for all these algorithms. We use the same 4 filters (first and second derivatives horizontally and vertically) as [20, 21] does to extract the high-frequency component of LR images as input features. The magnification factor is 3 and the size of LR patches is set to 3×3 . The number of support bases of MSSR and is set to 10, same as the neighborhood number of NE [17], and the sparsity parameter of SC [20, 23] is set to 0.1. For our MCSR, the neighborhood size clustered to an atom is set to 2048 as [31] recommends; the number of support bases is changed to verify the reconstruction quality under different conditions. The regularization parameters λ_1 , λ_2 , α and β are empirically set to 0.1, 0.15, 0.3, and 10, respectively. We evaluate the performance of reconstruction on the same common datasets (Set5, Set14). All these procedures are implemented in MATLAB with a 2.4 GHz Intel i7 CPU and 8 GB memory.

Table 1 summarizes the results, showing PSNR and SSIM values of different methods. We can see that our normal MCSR method that uses ten support vectors as MSSR does has already outperformed other algorithms in most cases. The global MCSR method further surpasses the normal one in both average PSNR values and SSIM, which means we recover most details that are similar to the original HR images while demonstrating the best structural similarity with the original HR images. All these experimental results verified the effectivity and necessity of our MCSR method with collaboration representation compared to the previous MSSR framework.

Visual results are shown in Figs. 2, 3 and 4, demonstrating how MCSR has a visual performance comparable or superior to the other compared methods at a magnification of 3 on a couple of images. We can clearly observe that our proposed method provide the best visual plausibility on all images. In detail, NE [17] suffers a lot from unpleasant artifacts and block effects in all results. Yang et al.'s [20] method introduces some noise and suppresses the texture details due to the strong constraint of same sparse representation on the couple-learned LR and HR dictionary. Zeyde et al.'s [23] method and MSSR ease this problem; therefore, they both obtain a good result; however, they still do not recover enough details. For [23], it may because the several chosen sparse vectors are not able to represent complex image patterns, and for MSSR, it may refer to the insufficiency of manifold precision, where the manifold is

approximated by sparse support vectors. We can conclude that our MCSR reconstructs HR images more faithful to the originals with sharper edges, finer textures and less artifacts. This is owing to our collaboration support framework, which is more powerful and flexible to represent complex image patterns.

We further compare the running time for all these methods; the results are shown in Fig. 5. The NE [17] method costs more than 1000s due to the k -NN search in a large dataset. By learning a compact dictionary, Yang et al.'s method [20] and MSSR successfully shorten the time cost to a level below 100 s. However, they are still far from practical use. Zeyde et al.'s method efficiently boost the process using OMP to select several dictionary atoms for the input LR patch representation instead of solving complex L_1 optimization problem. Although our normal MCSR method is similar to the MSSR framework, the running time is still shortened using collaboration representation support. Note that, if 320 support vectors are used in our manifold-preserving process, although we can obtain best reconstruction quality, the time cost will be horrible due to enormous L_1 graph-solving process. This problem can be perfectly eased by our global solution, which costs only around 0.8 s while making no compromise to the reconstruction quality, therefore, leading to a very efficient solution for single-image SR problem. Therefore, the time computational complexity of the proposed method is much lower than that of other methods.

5 Conclusion

In this paper, we proposed a new SR strategy named manifold-regularized collaboration representation support regression (MCSR) to overcome the limitations of optical systems. By combining the collaboration representation of the training samples into the previous manifold-preserving framework, we obtain a much more precise manifold than MSSR. Furthermore, we proposed a global solution for our MCSR framework by transferring the whole mapping matrix calculation process into offline, therefore, increasing the online execution speed by 100 times. Experimental results show our MCSR method can provide a substantial improvement in reconstruction quality than other algorithms, with more faithful details and less artifacts. Simplifying the manifold-preserving process and improving the manifold mapping precision will be our future work.

Table 1 SR performance comparison in terms of PSNR (dB) and SSIM (bold for highest, Italics for second-highest)

Images	Scale	Bicubic		Yang's [23]		Zeyde's [26]		SF [30]		ANR [32]		A+ [31]		SRCNN [31]		Our EA	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Plane	x2	39.62	0.9835	–	–	42.57	0.9887	42.51	0.9885	42.44	0.9883	43.94	0.9901	43.75	0.9896	44.15	0.9902
Crow	x2	31.62	0.9531	–	–	34.55	0.9698	34.13	0.9679	34.10	0.9677	36.00	0.9762	36.03	0.9738	36.20	0.9766
Man	x2	34.51	0.9663	–	–	38.22	0.9761	38.18	0.9769	38.29	0.9772	39.51	0.9794	38.38	0.9773	39.65	0.9794
Butterfly	x2	27.43	0.9154	–	–	30.57	0.9531	30.27	0.9519	30.48	0.9514	32.01	0.9644	32.20	0.9605	32.28	0.9658
Monarch	x2	32.94	0.9601	–	–	35.69	0.9732	35.57	0.9714	35.71	0.9729	37.01	0.9768	37.18	0.9756	37.23	0.9772
Ppt3	x2	26.87	0.9450	–	–	29.26	0.9686	28.98	0.9660	28.97	0.9660	30.09	0.9776	30.40	0.9750	30.29	0.9789
040 (urban)	x2	22.23	0.8908	–	–	25.28	0.9465	25.00	0.9413	24.96	0.9413	27.02	0.9683	28.32	0.9699	27.64	0.9718
043 (urban)	x2	24.94	0.9169	–	–	29.16	0.9601	28.61	0.9538	28.65	0.9537	31.21	0.9729	31.47	0.9713	31.63	0.9743
081 (urban)	x2	30.72	0.9534	–	–	35.60	0.9823	35.24	0.9800	35.26	0.9799	37.93	0.9880	36.81	0.9851	38.38	0.9888
Average	x2	30.10	0.9427	–	–	33.43	0.9687	33.17	0.9664	33.19	0.9665	34.97	0.9771	34.95	0.9753	35.27	0.9781
Plane	x3	36.66	0.9708	38.24	0.9743	38.71	0.9777	38.64	0.9768	38.57	0.9767	40.18	0.9814	39.79	0.9795	40.42	0.9818
Crow	x3	28.62	0.9113	30.23	0.9277	30.51	0.9349	30.24	0.9289	30.20	0.9289	31.80	0.9478	31.61	0.9401	32.02	0.9494
Man	x3	30.16	0.9316	31.21	0.9305	32.62	0.9433	32.61	0.9484	32.77	0.9487	33.92	0.9557	33.54	0.9487	34.20	0.9570
Butterfly	x3	24.04	0.8216	25.58	0.8566	25.95	0.8782	25.60	0.9709	25.90	0.8717	27.24	0.9088	27.58	0.9008	27.47	0.9130
Monarch	x3	29.43	0.9198	30.71	0.9234	31.11	0.9394	30.91	0.9373	31.09	0.9377	32.14	0.9471	32.39	0.9447	32.34	0.9486
Ppt3	x3	23.71	0.8746	24.98	0.9012	25.25	0.9109	25.05	0.9026	25.03	0.9025	26.09	0.9342	26.02	0.9233	26.24	0.9377
040 (urban)	x3	19.09	0.7584	20.15	0.8055	20.84	0.8415	20.76	0.8321	20.75	0.8321	21.68	0.8812	22.39	0.8874	22.14	0.8943
043 (urban)	x3	21.64	0.8172	24.00	0.8588	24.51	0.8963	24.22	0.8757	24.14	0.8755	26.27	0.9235	26.21	0.9217	26.58	0.9287
081 (urban)	x3	27.21	0.8948	29.63	0.9303	30.34	0.9395	30.25	0.9375	30.26	0.9375	32.31	0.9584	31.82	0.9553	32.70	0.9611
Average	x3	26.73	0.8779	28.30	0.9009	28.87	0.9180	28.70	0.9122	28.75	0.9124	30.18	0.9376	30.15	0.9335	30.46	0.9413
Plane	x4	34.89	0.9599	–	–	36.37	0.9674	36.26	0.9661	36.20	0.9659	37.42	0.9724	37.27	0.9705	37.59	0.9731
Crow	x4	26.99	0.8783	–	–	28.42	0.8957	28.15	0.8940	28.12	0.8939	29.32	0.9188	29.18	0.9085	29.55	0.9224
Man	x4	27.31	0.8938	–	–	29.29	0.9171	29.31	0.9151	29.42	0.9152	30.18	0.9270	29.83	0.9211	30.48	0.9295
Butterfly	x4	22.10	0.7369	–	–	23.55	0.7883	23.29	0.7877	23.52	0.7886	24.42	0.8390	25.07	0.8410	24.65	0.8470
Monarch	x4	27.46	0.8808	–	–	28.73	0.9001	28.55	0.8999	28.70	0.9003	29.39	0.9122	29.89	0.9121	29.53	0.9145
Ppt3	x4	21.98	0.8126	–	–	23.09	0.8391	22.88	0.8366	22.85	0.8365	23.64	0.8764	23.84	0.8658	23.85	0.8818
040 (urban)	x4	17.04	0.6158	–	–	18.14	0.6914	18.09	0.6890	18.07	0.6890	18.25	0.7248	18.98	0.7301	18.48	0.7411
043 (urban)	x4	19.54	0.7114	–	–	21.66	0.7855	21.45	0.7779	21.40	0.7778	22.96	0.8488	23.17	0.8453	23.20	0.8587
081 (urban)	x4	25.07	0.8321	–	–	27.47	0.8851	27.40	0.8846	27.41	0.8846	28.98	0.9190	28.45	0.9144	29.38	0.9239
Average	x4	24.71	0.8135	–	–	26.30	0.8522	26.15	0.8501	26.19	0.8502	27.17	0.8820	27.30	0.8788	27.41	0.8880

Fig. 2 Visual qualitative comparison for 'butterfly' image from Set5 with magnification $\times 3$

Fig. 3 Visual qualitative comparison for 'lenna' image from Set14 with magnification $\times 3$

Fig. 4 Visual qualitative comparison for ‘pepper’ image from Set14 with magnification $\times 3$

Fig. 5 The average PSNR and running time cost on Set14 images using different methods

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